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Research papers

How does the quantification of uncertainties affect the quality and value of flood early warning systems?

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ABSTRACT

In an operational context, efficient decision-making is usually the ultimate objective of hydrometeorological forecasts. Because of the uncertainties that lay within the forecasting process, decisions are subject to uncertainty. A better quantification of uncertainties should provide better decisions, which often translate into optimal use and economic value of the forecasts. Six Early Warning Systems (EWS) based on contrasted forecasting systems are constructed to investigate how the quantification of uncertainties affects the quality of a decision. These systems differ by the location of the sources of uncertainty, and the total amount of uncertainty they take into account in the forecasting process. They are assessed with the Relative Economic Value (REV), which is a flexible measure to quantify the potential economic benefits of an EWS. The results show that all systems provide a gain over the case where no EWS is used. The most complex systems, i.e. those that consider more sources of uncertainty in the forecasting process, are those that showed the most reduced expected damages. Systems with better accuracy and reliability are generally the ones with higher REV, even though our analysis did not show a clear-cut relationship between overall forecast quality and REV in the context investigated.

1. Introduction

Floods are one of the most devastating natural disasters in the world (CRED and UNISDR, 2015). Related socio-economic impacts are considerable and require adequate prevention measures. Governments and communities seek to reduce the risk of floods, notably when the societal vulnerability is high in urban and industrial zones or when environmental and agricultural areas need to be protected, by locally implementing flood mitigation measures.

Traditionally, risk reduction is preferred over relief for economic and human considerations (Rogers and Tsirkunov, 2010). Skillful Early Warning Systems (EWS) have the capability to offer flood prevention by issuing warnings up to several days before the flood event. Recent studies have demonstrated that flood warnings are economically efficient (e.g. Priest et al., 2011; Molinari and Handmer, 2011; Verkade and Werner, 2011; Perrels et al., 2013). Frei (2010) estimated that benefits generated by weather services in Switzerland amount to some hundreds of millions of US$ per year. Similar results were obtained by Anaman and Lellyett (1996), Lazo and Chestnut (2002), Leviäkangas et al. (2007) in other industrialized countries, with ratios of invested and saved money ranging between 1:4 and 1:6. Pappenberger et al. (2015) evaluated that the European Flood Awareness System (EFAS, Thielen et al., 2009; Bartholmes et al., 2009), which provides information to national authorities and to the Emergency Response Coordination Center of the European Commission up to 15 days ahead, reaps benefits as high as 400 Euros for every 1 Euro invested.

In order to be valuable, forecasts from an EWS need to integrate the uncertainties inherent to the forecasting procedure. These uncertainties should reflect the inaccuracies that lay in the mathematical representation of the hydrometeorological system and in our knowledge of the initial and future states of the system (e.g. Ajami et al., 2007; Salamon and Feyen, 2010; Liu and Gupta, 2007; Liu et al., 2012). Ensemble prediction systems (EPS) provide a practical answer to incorporate different sources of uncertainty in the forecasting process. This approach has gained popularity and has been increasingly used by operational agencies (see the review by][and the online portal of the HEPEX community at www.hepex.org Cloke and Pappenberger, 2009). In a decision-making context, EPS-based forecasting systems have proved to be efficient and capable of improving the forecast value upon traditional deterministic forecasts (e.g. Richardson, 2000; Zhu et al.,

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2002; Verkade and Werner, 2011; Boucher et al., 2012; Stephens and Cloke, 2014), even if the communication of probabilistic forecasts in real-time remains a challenge (Ramos et al., 2010; Demeritt et al., 2013; Pagano et al., 2014).

Many authors have studied the quality of EPS-based forecasts, with first a focus on comparing deterministic and EPS forecasts. Forecast quality assessment has then evolved to assess the improvements in the quality of the forecasts when data-assimilation or post-processing techniques were applied to better quantify forecast uncertainty (e.g., Reggiani et al., 2009; Weerts et al., 2011; Bourgin et al., 2014; Boucher et al., 2015; Roulin and Vannitsem, 2015). Although studies assessing forecast quality are numerous, the assessment of the economic value of EPS-based flood forecast is still rare. In general, existing works have investigated how economic gains vary from using deterministic forecasts in a decision-making model that maximizes gains or minimizes losses over time, with respect to using probabilistic forecasts (Roulin, 2007; McCollor and Stull, 2008; Van den Bergh and Roulin, 2010; Muluye, 2011; Verkade and Werner, 2011; Boucher et al., 2012)). Additionally, the economic value of a forecast or a forecasting system is often tackled alone and the relation between quality and value is rarely addressed. As Verkade and Werner (2011) point out, it is expected that these aspects, quality and value, are linked, but more efforts should be put into clarifying what quality attributes of a forecast need to be improved to also improve its value.

Attempts to realistically define the damage associated to a particular river stage and the avoided losses from flood prevention measures are subject to many approximations and errors, and limited by the definition of the spatial and temporal boundaries of the event (Merz et al., 2010). The intangible costs resulting from deaths or traumas, for instance, are hard to quantify economically. When damages are tangible, the evaluation of costs is more straightforward but also subject to approximations since it may be difficult to take into account the indirect consequences of floods. To properly quantify damages, the approach to be adopted has to be sufficiently holistic to encompass all effective consequences, which can be social, political, and environmental (Merz et al., 2010).

To assess the economic gains related to protected values, Parker et al. (2007) use an estimation of the proportion of moveable inventory within a property. The main limitation of this approach is the fact that there are plenty of other measures, potentially more efficient to prevent damage losses. Moreover, flood warnings are not systematically followed by the population and efficient preventing measures are not always taken. More generally, decisions are made under constraints and can be encumbered by cues that are fallible, ambiguous, and altered by judgment (Choo, 2009).

The challenges mentioned above called for the use of the concept of maximum potential reduction of flood damage, which relates the actual flood damage avoided to other factors that stand in the way of optimal mitigation (Parker, 1991). The relation is defined as the product of the maximal potential reduction for a perfect system, the probability that the forecast is issued sufficiently in advance to react, the fraction of concerned people that will respond to the warning, and the fraction of people who will take effective measures. This product is estimated to 0.5 in the UK by the Department for Environment, Food and Rural Affairs (Verkade and Werner, 2011).

In order to avoid the cumbersome calculation of the maximum potential reduction damage, which would be particular to each studied location and would require a high number of approximations, the Relative Economic Value (*REV*) and the cost-loss ratio are often used. They are suitable to compare more easily different forecasting systems and to apply the methodology systematically to a large dataset of catchments. The *REV* is a more theoretical assessment of the value of a forecast. It is not based on real damage statistics but it can be easily transferable to more practical cases.

This study investigates how the quantification of uncertainties affects the quality of a decision. Six EWS were created using a framework hereafter named HOOPLA (HydrOlOgical Prediction LAboratory), which is a collection of hydrometeorological tools that allows constructing forecasting systems of various levels of complexity and sophistication. A simple framework is adopted to evaluate the economic gain that could be reached by the six EWS of different forecast quality. These systems differ by the way they take into account the main sources of uncertainty that play a role in hydrometeorological forecasting and, thus by the amount of total uncertainty they handle. As a result, they vary in terms of forecast performance, with different degrees of forecast accuracy, and reliability. We investigate their economic value and the contribution of their uncertainty components. The framework provides an estimate of the system's complexity required to take "better" decisions. From the results obtained, we also investigated if the quality of a hydrometeorological forecasting system, measured by typical scores, can be directly related to its economic value, as measured by the relative economic value (*REV*).

Section 2 presents the methodology, including the hydrometeorological data, the framework for the REV assessment, and the forecasting systems investigated. Results are presented in Section 3, where the REV and the relation between forecast quality and value are assessed. Concluding remarks are provided in Section 4.

2. Data and methodology

2.1. Catchment dataset and hydrometeorological data

The hydrometeorological dataset is composed of 20 catchments situated in the Province of Québec, Canada (Fig. 1). On these catchments, snow accumulation and melting are driving processes that create a spring freshet, while a second rain-induced flood peak may occur during fall. The catchment size and the mean annual streamflow vary from 512 to 15342 km^2 and from 8 to 300 $m^3 \cdot s^{-1}$, respectively.

2.1.1. Cost-loss ratio

The cost-loss ratio (*CLR*) represents the ratio of the costs of mitigation and the avoidable losses due to an adverse event. It is defined as:

$$CLR = r = \frac{C}{L_a} \quad (1)$$

where C is the cost of the warning response, and L_a the avoidable losses. In the following, results are presented for values of *CLR* comprised within the interval $0 < CLR \leqslant 1$, as, economically, it does not make sense to take preventive measures that are more expensive than avoidable damages. Moreover, the *CLR* cannot equal 0 since operating an EWS already implies some costs. A hypothetical case of *CLR* equal zero would imply that the system could benefit from a continuous warning that has no cost. In practice, the cost-loss values are situated in a narrower range, but with the use of the aforementioned interval for the *CLR*, we can draw a more general conclusion based on our different EWSs and study areas. This range of CLR is also more convenient for our purposes as it can theoretically encapsulate different costs (e.g., costs to set/initialize the EWS, costs of operation, and costs associated with the mitigation of the event) and all sources of avoidable loss. Therefore, a wide range of potential cases can be built upon this synthetic assessment of the value of *CLR*.

2.1.2. Relative economic value

The Relative Economic Value (*REV*) is a dimensionless factor that scales between the case where no forecast is issued (thus no